The Information Content of Cost Behavior Components:

Evidence from Labor Market Flows

Abstract

We examine the information content of cost behavior components in firms' asymmetric cost function, namely, aggregate-level elasticities of costs with respect to sales increases vs. decreases. We show that the persistence of the elasticity of costs is higher for sales increases than for sales decreases. Using business-level job flows from the Business Employment Dynamics (BED) dataset, which has recently been made available by the BLS, we find that, after accounting for GDP growth and other macroeconomic indicators, the aggregate elasticity of costs with respect to sales increases explains gross job inflows, but not gross job outflows. On the other hand, the aggregate elasticity of costs with respect to sales decreases explains gross job outflows, but not gross job inflows. When we include both elasticities in the regression, both are significant but with opposite signs. We obtain similar results in vector autoregression (VAR) models. Additional tests indicate that: (a) the effect of aggregate elasticity of costs with respect to sales decreases is more pronounced in periods with high uncertainty; and (b) asymmetric cost models explain more of the variation in job outflows than models that assume symmetric cost responses.

1. Introduction

A growing body of literature, beginning with Anderson, Banker, and Janakiraman (2003) (hereinafter ABJ), studies cost behavior and assumes a non-symmetric relation between costs and activities: costs increase more when activity rises than they decrease when activity falls by an equivalent amount. In particular, the literature estimates a log-linear cost function to capture the asymmetry, with a separate coefficient for firms that experienced an increase in sales (hereinafter β_{SU}) and an incremental coefficient for firms that experienced a decrease in sales during the period (hereinafter β_{SD}). These coefficients are interpreted in the literature as the elasticity of costs to increasing or decreasing sales. In this paper, we study the information content of both coefficients at the aggregate level, by focusing on business-level job-flows.

We use the Business Employment Dynamics (BED) quarterly data on job flows provided by the Bureau of Labor Statistics (BLS). While traditional employment data, which are based on the Current Population Survey (CPS), are gathered at the worker level, the BED data are collected at the business (i.e., the firm or establishment) level.[1] Boon, Carson, Faberman, and Ilg (2008) argue that, compared with other sources of employment data, the BED data are more appropriate for analyzing the business side of the labor market because they provide information on positions and not employees. Furthermore, the BED data provide flow information, in particular, gross inflows and outflows of jobs each quarter. Studying job inflows and outflows separately allows us to better evaluate the differential impact of firms' cost behavior components. We also note that the BED data are available with a lag of three quarters and hence are less timely than the CPS data, which are compiled every month and released at the beginning of the following month. Because

[1] The data cover all establishments covered by State unemployment insurance programs.

our focus in this paper is to understand how cost behavior components relate to the labor market, rather than forecasting of unemployment *per se*, the BED data fit our purpose.

We estimate quarterly time-series of aggregate-level β_{SU} and β_{SD} for all public firms in the United States for the period Q3:1992 to Q2:2017. Prior literature suggests that the two coefficients capture different aspects of firms' cost behavior. β_{SU} captures the elasticity of changes in costs to increases in sales, with a greater coefficient reflecting more elastic (less rigid) cost structure (Lev 1974; Noreen 1991; Kallapur and Eldenburg 2005; Aboody, Levi and Weiss 2018). As such, it reflects managers' long-term capacity and production-technology choices and cannot be easily altered in the short-run. β_{SD} captures the incremental resource retention when sales decrease—that is, the difference between change in costs when sales increase and change in costs when sales decrease by an equivalent amount. By its very nature, this coefficient reflects the level of adjustment costs to reduce or restore committed resources as well as short-term managerial expectations (ABJ 2003). Both coefficients are determined by the current production technology, capacity choices, level of adjustment costs, and managers' discretion when making decisions about resources. Yet, β_{SU} is likely to reflect the elasticity of the production technology and managers' long-run operational and capacity choices to a larger extent, while β_{SD} is more likely to capture adjustment costs and managerial short-term expectations.[2]

We begin our analysis by studying the time-series properties of each coefficient, by estimating its persistence over time. We expect the persistence of the aggregate elasticity of costs with respect to sales increases (β_{SU}) to be higher than the persistence of the aggregate elasticity of costs with respect to sales decreases (β_{SD}), for the following reasons. First, sales decline is typically

[2] There are vast literatures on $\beta_{SD,}$ the stickiness coefficient, and also on the coefficient of a symmetric cost function. β_{SU}, *per se*, has not been studied extensively, and hence we draw from the literature on firms' cost structure when we interpret this coefficient.

only temporary. Hence, at the aggregate level, the composition of firms experiencing declining sales is likely to change substantially from one quarter to the next. Second, at the firm level, β_{SU} is likely to reflect long-term decisions, such as the choice of capacity and production technology, while the decision to cut down resources, reflected in β_{SD} is more short-term in nature and is typically made only after reduced demand realization is observed. Our findings indicate that both coefficients are highly persistent, which is to be expected because they reflect aggregate elasticities. Consistent with our expectations, we also find that the persistence of β_{SU} is higher than the persistence of β_{SD}.

We next examine the explanatory power of each coefficient individually. We regress contemporaneous gross job inflow and outflow rates on the aggregate β_{SU} and β_{SD} coefficients and control variables. We find that β_{SU} is related to gross job inflow rate, but not gross job outflow rate. Conditional on GDP growth and other macroeconomic indicators, a larger β_{SU} entails a greater increase in resources, and hence greater job inflows. β_{SU} fails to predict the gross job outflow rate due to the asymmetric nature of cost behavior. Specifically, the actual reduction in resources is likely to be different from the one predicted by β_{SU}, due to cost stickiness. We also find that β_{SD} is negatively related to gross job outflows but is not related to inflows, consistent with β_{SD} reflecting resource retention decisions. Conditional on macroeconomic indicators, a larger β_{SD} entails greater resource retention and hence less job outflows.

When we include both coefficients in the regression, we find that they both predict gross job inflow and outflow rates, but with opposite signs. β_{SU} is positive, whereas β_{SD} loads negatively. Conditional on the inclusion of β_{SD}, GDP growth, and other macroeconomic indicators, a larger β_{SU} indicates greater job inflows and job outflows because of the greater elasticity of the cost function. Conditional on the inclusion of β_{SU} and macroeconomic indicators, a larger β_{SD} indicates less job outflows, but also less job inflows due to the higher level of adjustment costs to reduce or restore committed resources that affect both contraction and expansion. Moreover, the coefficient on β_{SU} is always larger in absolute value than the coefficient on β_{SD}. This result is consistent with the greater persistence of β_{SU} compared with $\beta_{SD.}$

Having documented the information content of the two macro-level elasticities using contemporaneous job flows, we now examine their relationship to future job flows. Given the high persistence of both coefficients, we expect that they will explain not only contemporaneous flows, but also future ones. Indeed, both coefficients predict future flows up to four quarters ahead.

We next examine second moment properties of the β_{SD} coefficient. We interpret the standard error of the estimated β_{SD} coefficients—SE(β_{SD})—as indicating uncertainty. A higher value of this standard error implies a less precise β_{SD} estimate, which indicates greater dispersion among firms in their level of resource retention, which in turn reflects different opinions about future macroeconomic conditions. We examine whether the explanatory power of β_{SD} varies with uncertainty. We find that the standard error of the estimated β_{SD} coefficient is higher at the onset of recessionary periods, consistent with the higher level of uncertainty, and that, conditional on β_{SD}, higher standard error of β_{SD} is associated with less job outflows, indicating greater employee retention in periods of high uncertainty.

Finally, we compare the model assuming an asymmetric cost behavior (i.e., sticky costs) to a traditional model that assumes symmetry. To do so, we estimate the time series of $\beta_{SYM},$ which assumes a symmetric relation between change in costs and increases and decreases in sales. We then use β_{SYM} in the regressions of gross job inflow and outflow rates. We find that, for a given level of GDP growth and conditional on macroeconomic indicators, a larger β_{SYM} is associated with greater job outflows as well as greater job inflows.

We compare the explanatory power of a model that includes β_{SYM} to a model that includes both β_{SD} and β_{SU}, by examining the R-squared of the two models. Vuong (1989) tests indicate a statistically significant improvement in the R-squared of the asymmetric cost model when explaining the gross and net job outflow rates, but not the gross job inflow rate, consistent with the information content of β_{SD} reflecting the sticky nature of costs.

We augment the OLS results by estimating vector autoregression (VAR) models. The VAR approach takes into account time-series interdependencies of the different variables of interest. One major disadvantage of VAR models, however, is the need to estimate a very large number of coefficients (Robertson and Tallman 1999). In particular, compared to an OLS regression, the number of cross-sectional predictors that a VAR model can handle is relatively limited, because the number of coefficients to be estimated grows exponentially with the number of variables. We run a reduced-form VAR, which builds on Okun's law (Okun 1963). Okun's law documents a robust negative relationship between output (*GDP*) growth and unemployment rate changes. We decompose the change in unemployment rate into gross job inflow rate and gross job outflow rate, and we include the β_{SU} and β_{SD} coefficients. Results from the VAR analysis are in line with the conclusions from the OLS regressions.

This paper contributes to several streams of literature. First, we contribute to the cost accounting literature on sticky costs (Anderson, Banker, and Janakiraman 2003; Banker and Chen 2006; Anderson, Banker, Huang, and Janakiraman 2007; Weiss 2010; Kama and Weiss 2013; Rouxelin, Wongsunwai, and Yehuda 2018). To the best of our knowledge, we are the first to examine the differential information content (with respect to the labor market) of aggregate cost elasticities to sales increases (β_{SU}) and sales decreases (β_{SD}). Our study employs a relatively new dataset that has been understudied in the literature—the BED dataset—and includes information about job flows at the firm level and hence is more suitable to analyze firms' cost structure. Furthermore, we compare the symmetric and the asymmetric costs models at the aggregate level and show the incremental informativeness of the asymmetric cost behavior model.

Second, we contribute to the macroeconomics literature on unemployment rate. We show how the aggregate cost elasticity to sales increases (β_{SU}) and sales decreases (β_{SD}) relate to job inflows and outflows in business establishments. Recent research on unemployment forecasting emphasizes the importance of separately predicting each type of flow. Using the refined BED data at the establishment level, we are better able to assess separately the effect of each of the coefficients β_{SD} and β_{SU}.

Third, our paper integrates a cost accounting research topic, asymmetric cost behavior, with the financial accounting literature on the usefulness of aggregate accounting information in predicting the macroeconomy (e.g., Jorgensen, Li, and Sadka. 2012; Konchitchki and Patatoukas 2014; Gallo, Hann, and Li 2016; Nallareddy and Ogneva 2017). The importance of integrating insights from financial and managerial accounting research and other literatures has long been acknowledged (e.g., Hemmer and Labro 2008; Banker and Byzalov 2014).

The remainder of the paper proceeds as follows. We review related literature and develop our main prediction in Section 2. Section 3 describes the data and provides descriptive statistics. Sections 4, 5 and 6 present the results of the analysis. Section 7 concludes.

2. Related Literature and Main Prediction

2.1 The Information Content of Cost Behavior Components

A growing body of literature, beginning with ABJ (2003), studies cost behavior and assumes a non-symmetric relation between costs and sales: costs increase more when activity rises than they decrease when activity falls by an equivalent amount. In particular, the literature captures the asymmetry by estimating a log-linear cost function, with a separate coefficient for firms that experienced an increase in sales (β_{SU}) and an incremental coefficient for firms that experienced a decrease in sales during the period (β_{SD}).

Prior research has studied the coefficients at the firm level. β_{SU} is typically interpreted as elasticity of cost to increases in demand — that is, the percentage change in costs for a 1 percent increase in sales.[3] A higher slope indicates a more elastic cost structure with a lower proportion of fixed costs and a higher proportion of variable costs, or a lower operating leverage (Lev 1974; Cooper and Kaplan 1987; Noreen and Soderstrom 1994, 1997; Kallapur and Eldenburg 2005; Banker, Byzalov, and Plehn-Dujowich 2013). The lower the slope coefficient, the more rigid is the firm's cost structure. Additionally, β_{SU} can also be interpreted as the ratio of marginal cost to average cost (Noreen and Soderstrom 1994) or the ratio of variable costs to total costs if total costs are linear in volume (Kallapur and Eldenburg 2005).

A more elastic cost structure offers companies greater flexibility because it involves fewer upfront cost commitments (i.e., fewer fixed costs). A firm's cost structure is determined by its production technology. Yet, firms can transform fixed costs into variable costs via a process of variabilization. Under this process, activities involving higher fixed costs are outsourced. Recent managerial accounting papers study how the business environment in which the firm operates

[3] A large literature studies this coefficient. Yet, this literature assumes a symmetric cost function. The cost stickiness literature, on the other hand, has mainly studied the properties of the incremental β_{SD} coefficient.

affects its cost rigidity. Using data from the hospital industry, Kallapur and Eldenburg (2005) and Holzhacker, Krishnan, and Mahlendorf (2015) identify resource procurement choices made by hospitals facing higher demand uncertainty. These choices include the degree of outsourcing, the proportion of leased equipment versus owned equipment, and the proportion of contract labor versus fixed-term salaried employees.

In contrast, Banker, Byzalov, and Plehn-Dujowich (2013) demonstrate that, in response to higher demand uncertainty, firms choose a more rigid short-run cost structure. They assume a production technology with a fixed capacity resource that is chosen in advance and a variable resource that is chosen after the demand is realized. When demand is unusually high relative to capacity, the firm bears high congestion costs due to strained capacity. Consequently, managers prefer to commit sufficient capacity in advance to avoid excessive congestion costs, which can considerably reduce the firm's profitability.

The β_{SD} coefficient has also been studied in the literature on cost stickiness. ABJ (2003) argue that this coefficient captures the effect of deliberate managerial decisions about committed resources when there is uncertainty about future demand for their firms' products. In particular, greater magnitude of adjustment costs leads to greater cost stickiness because the firm's behavior under optimal decision-making is asymmetric. With labor, severance and training costs can be significant. Faced with declining sales, managers are reluctant to fire workers because retaining the unused resources helps avoid the large staff termination costs and future training costs when rehiring. Conversely, when activity increases, although managers may be reluctant to hire more workers because of the adjustment costs, the increase in current sales can only be achieved if additional workers are hired, thus the reluctance effect is likely to be more muted (Banker and Byzalov 2014; Banker, Byzalov, and Chen 2013).

The literature has offered additional explanations for this coefficient. First, cost stickiness is indicative of managerial expectations regarding future demand for the firm's products (Banker, Byzalov, Ciftci, and Mashruwala 2014). Managerial optimism weakens cost response to current sales decreases and amplifies cost response to current sales increases, thereby resulting in increased cost stickiness. Second, cost stickiness can be the result of managers' empire-building incentives to maximize resources under their control. Larger resources can give managers more power, potentially higher compensation, and other perquisites (Anderson, Banker, and Janakiraman 2003; Chen, Lu, and Sougiannis 2012; Kama and Weiss 2013). Empire-building managers will cut resources only moderately when sales decrease and will expand resources excessively when sales increase.

2.2 Empirical Prediction

We expect the two beta coefficients to capture different aspects of firms' cost behavior. β_{SU} captures the elasticity of changes in costs to increases in sales, with a greater coefficient reflecting more elastic (less rigid) cost structure. This coefficient is the result of managers' long-term decision about capacity and production technology, and cannot be easily altered. β_{SD} captures the incremental resource retention when sales decrease—that is, the difference between change in costs when sales increase and change in costs when sales decrease by an equivalent amount. As such, this coefficient reflects the level of adjustment costs to reduce or restore committed resources as well as managerial discretion (ABJ 2003). Moreover, the decision to scale down resources is often made after observing demand realization, and hence this decision is more short-term in nature.

Both coefficients are determined by the current production-technology, capacity level, adjustment cost level, and managers' discretion when making resource-decisions. Yet, β_{SU} is likely to reflect the elasticity of the production technology to a larger extent, while β_{SD} is more likely to capture adjustment costs and short-run managerial expectations. This is because the cost structure of the firm (i.e., β_{SU}) is the result of managers' long-term capacity and operational choices. Indeed, Holzhacker, Krishnan, and Mahlendorf (2015) argue that changes to a firm's cost structure usually require modifications to the firm's operations that are not easily reversible. In contrast, cost stickiness reflects managers' short-term decisions to retain unused resources, and hence is more likely to capture timelier managerial expectations (Banker, Byzalov, and Plehn-Dujowich 2013).

3. Data

3.1 The Business Employment Dynamics (BED) Data

We obtain quarterly data on job inflows and outflows from the Business Employment Dynamics (BED) dataset provided by the Bureau of Labor Statistics (BLS). The BED contains longitudinally-linked administrative records for all establishments covered by state unemployment insurance agencies.

Spletzer, Faberman, Sadeghi, Talan, and Clayton (2004) argue that, while the traditional unemployment rate identifies the overall growth or decline of the labor market, it does not convey the underlying heterogeneity of job inflows and job outflows at the establishment level. Job inflows are the sum of all employment increases at opening or expanding establishments. Job outflows are the sum of all employment losses at closing or contracting establishments.

3.2 The Sample

Our sample period is Q3:1992 to Q2:2017. We begin our sample in Q3:1992 because this is the earliest quarter covered by the BED dataset.[4] We collect quarterly financial statement data from the Compustat North America Quarterly Database. Since the BLS compiles the BED data on a quarterly basis, using quarterly data sources provides a natural alignment with the data generation process for the key dependent variables in our analyses.

We implement the methodology in ABJ (2003) to estimate β_{SU} and β_{SD}, by regressing the sum of SG&A expenses (Compustat data item *xsgaq*), and cost of goods sold (*cogsq*) on sales revenue (data item *saleq*). We combine expenses for COGS and SG&A to proxy for labor cost. We use available data for all U.S. industrial companies available on Compustat. In line with prior research (e.g., Banker and Byzalov 2014), we winsorize all continuous variables at 0.5% tails within each quarter and 2-digit SIC industry.

We estimate the following regression each quarter:

$$\log\left[\frac{(COGS+SG\&A)}{lag(COGS+SG\&A)}\right] = \beta_0 + \beta_1 \log\left[\frac{SALES}{lag(SALES)}\right] + \beta_2\, I\_Decrease \times \log\left[\frac{SALES}{lag(SALES)}\right] + \varepsilon \qquad (1)$$

In each calendar quarter q, we estimate regression (1) using Compustat firm-quarter data with fiscal quarters ending in [q–3, q]. We seasonally adjust changes in costs and sales. The indicator variable *I_Decrease* takes value 1 if seasonal change in quarterly sales (sales reported in the current quarter compared to four quarter ago) is negative and 0 otherwise. β_{SU} is equivalent to standardized β_1 (i.e., after subtracting sample mean of the estimated β_1 values and dividing by the sample standard deviation). β_{SD} is calculated as standardized β_2 multiplied by −1, to facilitate easier interpretation (higher value of β_{SD} indicates more sticky costs).

[4] The BED dataset first became publicly available in 2004. The data are updated on a quarterly basis, with a lag of three quarters.

3.3 Descriptive Statistics

Panel A of Table 1 reports descriptive statistics for the main variables used in the analysis. The gross job inflow rate, expressed as a percentage of total employment, had a mean value of 7.11% for our sample period, with a standard deviation of 0.82%. The gross job outflow rate, on the other hand, averaged 6.79% with 0.75% standard deviation.

We estimate β_1 and β_2 coefficients by running rolling OLS regression models following equation (1), using all Compustat industrial firms. The β_1 and β_2 estimates have means of 0.410 and -0.053, respectively. Thus, for a given quarter, firms report an average increase of 0.41% in their operating costs for every 1% increase in sales revenue, whereas firms report a cost decrease of only 0.36% (0.410% − 0.053%) per 1% decrease in sales revenue.

We next present descriptive statistics for the four sets of control variables that are known to explain the change in the level of unemployment (Rouxelin, Wongsunwai, and Yehuda 2018). All variables are defined in Appendix A. The first set of control variables captures the overall macroeconomy and includes the growth in real GDP (*GDP*), aggregate GAAP earnings (*Earn*), change in earnings (Δ*Earn*), stock market return (*MktRet*) and the industrial production index (*IPI*). We use estimates of real GDP growth rate as released by the Bureau of Economic Analysis. Over our sample period, this variable averaged 2.53% but with substantial variation (standard deviation of 1.95%). We also control for aggregate earnings ($Earn_t$), and stock market return ($MktRet_t$). The industrial production index (IPI_t), published by the Federal Reserve Board, measures the real output of all manufacturing, mining, and electric and gas utility establishment in the U.S.

Our second set of controls are proxies for different explanations of cost stickiness that have been identified in prior literature: (a) *BBD* Economic Policy Uncertainty (*EPU*) index, which captures the level of policy-related economic uncertainty (Baker, Bloom, and Davis 2014; Bloom

2014). This index is likely to be correlated with uncertainty about future activities, a potential driver of cost stickiness; (b) the University of Michigan Consumer Sentiment Index (*CSI*). This index gauges consumers' level of optimism or pessimism, which is likely to be correlated with managers' level of optimism or pessimism, another potential explanation for cost stickiness. The third set of control variables includes federal funds (i.e., interest) rate (*IR*) and inflation rate (*Inf*), following Taylor's (1993) rule.

Our final set of controls includes factors that have been proposed in prior literature as predictors of unemployment specifically (rather than of the macroeconomy as a whole), consisting of labor-force flows and labor reallocations.[5] The four-week average change in initial unemployment insurance claims (*UIC*) (people who filed for unemployment benefits for the first time during the previous month) and the composite Help-Wanted Index (*HWI*) (percentage of job openings or vacancies out of the total labor force) are proxies for labor flows, often used in policymaking (e.g., Barnichon 2010). Employment growth dispersion (Lilien 1982) and return dispersion (Loungani, Rush, and Tave 1990; Brainard and Cutler 1993; Nallareddy and Ogneva 2017) are proxies for performance dispersion.

Panel B of Table 1 presents the correlation matrix between the BED job flow rates and the change in the traditional unemployment rate, which is based on CPS responses. Change in unemployment rate is positively and significantly associated with net job outflow rate (difference between gross job outflow rate and gross job inflow rate). Furthermore, gross job inflow rate (gross job outflow rate) is negatively (positively) correlated with change in unemployment rate. Finally, there is a positive and significant correlation between gross job inflow rate and gross job outflow

[5] Lilien (1982) and Davis (1987) argue that unemployment is, in part, the result of worker turnover from declining to expanding sectors of the economy. Due to labor reallocation frictions related to job search, retraining, or physical relocation, changing jobs takes time, which leads to higher unemployment in the interim. High performance dispersion implies that some firms lay off employees while others recruit new workers.

rate, suggesting that periods of increased job inflows and outflows occur simultaneously and are therefore indicative of overall job redistributions in the economy.

4. The Information Content of Cost Behavior Components

4.1 Persistence over time

We begin by estimating the persistence of both beta coefficients, β_{SU} and β_{SD}, using AR(1) regressions of the coefficient on its lagged value. As both coefficients capture aggregate persistence, we expect the AR(1) coefficient to be statistically significant and close to 1. Yet, we expect the persistence of β_{SU} to be higher than the persistence of β_{SD} for the following reasons: First, a reduction in sales is likely to be temporary. Hence, the composition of firms experiencing such a decline is likely to change considerably form one quarter to the next, affecting the intertemporal variation of β_{SD}. Second, the decision to reduce committed resources when sales decrease, reflected in β_{SD}, is typically made after observing demand realization, and hence is likely to vary more over time compared with the decisions reflected in β_{SU}, which are more long-run in nature, and reflect decisions such as capacity and choice of production technology.

Table 2 presents the results. Column I shows the estimation of β_{SU}'s persistence. The magnitude of the coefficient is 0.99 and it is highly statistically significant. Column II shows that the persistence of β_{SD} is 0.93, and it is also statistically significant. The difference in coefficients is significant at the 5% level.

4.2 OLS Regressions

4.2.1 Contemporaneous Gross Job Inflow Rate

Next, we run OLS regressions of job inflows on the two beta coefficients, β_{SU} and β_{SD}. We include a battery of control variables. Additionally, because the beta coefficients are standardized, the interpretation of their incremental explanatory power is straightforward. We estimate three OLS regressions, nested in the following model:

$$\textit{Job flow rate} = \alpha_1 + \alpha_{2k}\,\beta_{SU} + \alpha_{3k}\,\beta_{SD} + \boldsymbol{\alpha}\ \textbf{\textit{Controls}} + \varepsilon, \tag{2}$$

where β_{SU} and β_{SD} are estimated in the current quarter q using data from public filings by listed U.S. firms with fiscal quarters ending in [q-3, q].[6] *Job flow rate* is either gross job inflow rate or gross job outflow rate. We apply the Newey-West procedure in order to obtain consistent standard errors in the presence of autocorrelation. We use a truncation parameter (or lag) of 3.[7]

Table 3, Column I, presents the results of a regression of the gross job inflow rate on β_{SU} and control variables. Consistent with our prediction, we obtain a positive association between β_{SU} and the contemporaneous gross job inflow rate. The coefficient is both economically and statistically significant. A one-standard-deviation-higher β_{SU} is associated with an increase of 38 basis points in the gross job inflow rate (the dependent variable, measured in percentage points). This effect is economically significant, given that the model includes all the control variables and the mean gross job inflow rate during the sample period is 7.11%.

We include a battery of control variables, known to explain the change in the level of unemployment (Rouxelin, Wongsunwai, and Yehuda 2018). These coefficients generally enter the

[6] We use quarterly data from quarter t-3 to quarter t to address potential complications due to seasonality, which affects many businesses. In robustness tests, we only use quarterly data in quarter t and our conclusions remain unchanged.
[7] The choice of 3 lags is based on the usual rule of thumb: $T^{0.25}$, where T is the number of observations. In our sample of 100 quarterly observations, this suggests a truncation parameter of 3. In robustness tests, we allow for different lag lengths and our conclusions remain unchanged.

regression with their expected sign. For example, the coefficients on *GDP* is positive and significant, consistent with Okun's law.[8] The coefficient on *MktRet* is negative and significant, contrary to our expectation, possibly as a result of the correlation between this variable and the other variables capturing the state of the overall economy (*GDP*, *Earn*, Δ*Earn*). The coefficient on *IPI* is negative and significant, consistent with greater uncertainty reducing future job inflows. *CSI* loads positively, confirming the positive relation between job inflows and consumer sentiment. *Ret_Disp* is strongly positive, consistent with labor reallocation frictions resulting in greater movement in the labor market.

In Column II, we estimate the regression with β_{SD} and control variables as the independent variables. The coefficient on β_{SD} is not significant at conventional levels, suggesting that there is no relationship between β_{SD} and the gross job inflow rate, consistent with the hypothesized information content of this coefficient.

Colum III presents the results of a regression which includes both beta coefficients. We find that β_{SD} loads positively, while β_{SD} loads negatively. Conditional on the inclusion of β_{SD}, GDP growth, and other macroeconomic indicators, a higher β_{SU} indicates more job inflows, because of the greater elasticity of the cost function. Conditional on the inclusion of β_{SU} and macroeconomic indicators, a larger β_{SD} indicates less job inflows due to the higher level of adjustment costs to reduce or restore committed resources that affect both contraction and expansion.

Both coefficients are larger in magnitude compared to the regressions in the first two columns, in which they are included individually, indicating that the inclusion of both coefficients increases both their economic and statistical significance. For example, the coefficient on β_{SU} is almost twice as large as its magnitude in Column I: conditional on β_{SD}, a one-standard-deviation-

[8] Okun (1963) documents a negative relation between unemployment and real GDP growth. In Table 3, we examine job inflows, which are positively related to real GDP growth.

higher β_{SU} is associated with an increase of 63 basis points in the gross job inflow rate, compared with an increase of 38 basis points documented in Column I.

Finally, the coefficient on β_{SU} is larger than the coefficient on β_{SD}. This finding is consistent with the greater explanatory power of $\beta_{SU.}$ Moreover, β_{SU} is more persistent than β_{SD} because the relative difficulty in adjusting the elasticity of costs with respect to sales increases at the firm level and at the economy level.

Overall, the results in Table 3 lend strong support to the different information content of β_{SU} and β_{SD}.

4.2.2 Contemporaneous Gross Job Outflow Rate

Table 4 repeats the analysis for the gross job outflow rate. Column I shows the results of a regression of the contemporaneous gross job outflow rate on β_{SU} and control variables. The coefficient of β_{SU} is not significant at conventional levels, suggesting that β_{SU} by itself does not explain the gross job outflow rate. This finding is consistent with aggregate-level cost stickiness—that is, for a given growth in GDP, firms are not likely to cut jobs at the level predicted by β_{SU} (in absolute value) because of adjustment costs and managerial discretion.

In Column II, we examine the information content of β_{SD}. The coefficient of β_{SD} is negative and significant, indicating that higher cost stickiness is associated with lower job outflows. The coefficient is also economically large. Conditional on GDP growth and other macroeconomic indicators, a one-standard-deviation-higher β_{SD} is associated with a decrease of 19 basis points in the gross job outflow rate. This effect is economically significant, given that the model includes all the control variables and the mean gross job outflow rate during the sample period is 6.79%.

As before, we include a battery of control variables, known to explain the change in the level of unemployment. These coefficients generally enter the regression with their expected sign. For example, the coefficients on *Earn*, Δ*Earn* and *MktRet* are negative and significant, indicating a negative relation between the state of the economy and job outflows, as we would expect. The coefficients on *EPU* and *IPI* are negative and significant, suggesting that in periods of high uncertainty, job outflows are smaller. We explore this issue in detail in section 4.3.

Unemployment insurance claims (*UIC*) is positively related to job outflows. Finally, the positive coefficient obtained for *IR* indicates a rise in unemployment following an interest-rate increase.

In Column III, we include both elasticities β_{SU} and β_{SD}. The coefficient on each of the elasticities is larger compared with Column I and II. Moreover, both coefficients are statistically significant. However, while β_{SU} is positively related to the gross job outflow rate, β_{SD} is negatively related to job outflows. Conditional on the inclusion of β_{SD}, GDP growth, and other macroeconomic indicators, a higher β_{SU} indicates a more elastic cost structure and hence more job outflows. Conditional on the inclusion of β_{SU} and macroeconomic indicators, a larger β_{SD} indicates less job outflows due to cost stickiness, which implies a lower decline in resources when sales decline, compared to the situation in which sales increase by an equivalent amount. As in Column III of Table 2, the coefficient on β_{SU} is larger than the coefficient on β_{SD} consistent with higher persistence and greater explanatory power of β_{SU} compared with β_{SD}.

4.2.3 Future Gross Job Outflow and Inflow Rates

In Table 5, we present the prediction analysis. Panel A shows results for predicting the job inflow rate in the subsequent four quarters. The control variables are included in the regressions but are not tabulated for parsimony. The evidence in Column I indicates that the coefficient on β_{SU}

is positive and significant at all horizons. This coefficient increases monotonically in quarters t+1 to t+3, and decreases in quarter t+4. The coefficient on β_{SU} is also economically large. Conditional on GDP growth and other macroeconomic indicators, a one-standard-deviation-higher β_{SU} is associated with an increase of 33 basis points in the gross job inflow rate in the next quarter, 36 basis points two quarters ahead and 37 basis points three quarters ahead.

Column II confirms that β_{SD} is not a predictor of gross job inflows at any prediction horizon, consistent with the results in Table 3. Column III shows results using both elasticities. The coefficients on both β_{SU} and β_{SD} are economically and statistically significant. Moreover, consistent with Panel A, β_{SU} loads positively, while β_{SD} loads negatively. The coefficient on β_{SU}, conditional on the inclusion of β_{SD} in the regression, is larger compared to Column I. Furthermore, the coefficient on β_{SU} is always larger than the coefficient on β_{SD}. This finding is consistent with the short-term nature of the information in the elasticity of costs with respect to sales decreases.

In Panel B, we explore the prediction of job outflow rates. Column I confirms the findings in Table 4 and indicates that β_{SU} does not predict gross job outflow rates. Column II indicates that β_{SD} predicts future job outflows at all horizons examined. The coefficient on β_{SD} decreases monotonically in quarters t+1 to t+3, and then increases. In Column III, when both coefficients are included in the regression, both load significantly, but with opposite signs at all horizons except for quarter t+4, when only the coefficient on β_{SD} is statistically significant at conventional levels.

Collectively, Tables 3 to 5 document the different information content of the aggregate-level elasticities of costs relative to sales increases vs. decreases. Moreover, when both are included in the same regression, these elasticities have an economically large explanatory power. The explanatory power of the elasticity of costs with respect to sales increase is larger than the elasticity with respect to sales decreases.

4.3 Standard Error of β_{SD}

Having studied the explanatory power of both the β_{SU} and β_{SD} coefficients, we next examine whether the explanatory power is greater in periods of high uncertainty. We use the second moment of the estimated β_{SD} coefficient—that is, the standard error, SE(β_{SD})—as a measure of the level of uncertainty.

A higher standard error of β_{SD} implies: (a) a less precise β_{SD} coefficient; and (b) a higher dispersion in the level of resource retention across firms, reflecting different expectations about future macroeconomic conditions. Under explanation (a), we expect a positive and significant interaction between β_{SD} and its standard error, consistent with less pronounced effect of β_{SD} on job outflows when the estimation of β_{SD} is less precise. Under (b), we expect a negative and significant interaction term, indicating that the impact of β_{SD} on job outflows is more pronounced in periods of high uncertainty.

Figure 1 depicts SE(β_{SD}) and the BBD Economic Policy Uncertainty Index. SE(β_{SD}) peaks during recessions, then declines when recovery occurs.

In Table 6, we regress gross job outflow rate on β_{SD}, SE(β_{SD}), and their interaction. SE(β_{SD})—top decile (quartile) is a dummy variable that takes a value of 1 if SE(β_{SD}) is in the highest decile (quartile) and 0 otherwise. As before, the coefficient on β_{SD} is negative and significant, suggesting that the higher β_{SD}, the higher is the employee retention by firms, and hence the lower are job outflows. The coefficient of SE(β_{SD}), the standard error of β_{SD}, is also negative and significant, consistent with a greater standard-error corresponding to a higher level of uncertainty.

The interaction term between β_{SD} and SE(β_{SD}) quantile is negative and significant, suggesting that the relationship between β_{SD} and job outflows is stronger when there is greater uncertainty. The results in column I show that, in quarters with high uncertainty (standard error of β_{SD} is in the highest decile), a one-standard-deviation-higher β_{SD} is associated with a decrease of 46.5 (-0.217 – 0.248) basis points in the gross job outflow rate (the dependent variable, measured in percentage points). Column II shows similar results when using quartiles of SE(β_{SD}) to construct the dummy variable.

4.4 Comparing the Symmetric and Asymmetric Cost Behavior Models

In Table 7, we compare the asymmetric cost model, introduced to the literature by ABJ (2003), to a symmetric cost model, which assumes the same response of costs (in absolute value terms) to a 1 percent increase or decrease in sales. We run the following seasonally-adjusted quarterly regression:

$$\log\left[\frac{(COGS+SG\&A)}{lag(COGS+SG\&A)}\right] = \beta_0 + \beta_3 \log\left[\frac{SALES}{lag(SALES)}\right] + \varepsilon \qquad (3)$$

We label the standardized β_3 coefficient from this regression β_{SYM}.

Table 7 compares the explanatory power of β_{SYM} to the explanatory power of both β_{SU} and β_{SD} for different job flow rates. Specifically, we compare the difference in adjusted R-squared between the two classes of models, and present Vuong (1989) Z-statistics to indicate whether this difference is statistically significant.

In Columns I and II we compare the two models' performance in explaining the gross job inflow rate. The coefficient of β_{SYM} in column II loads positively and significantly, suggesting that a higher β_{SYM}, conditional on GDP growth and other macroeconomic indicators, is associated with a greater job inflow rate. We do not find any difference between the adjusted R-squared of the symmetric and asymmetric models.

Columns III and IV repeat the analysis for gross job outflow rate. In this case, the coefficient of β_{SYM} is also positive and statistically significant, suggesting that a higher β_{SYM}, conditional on GDP growth and other macroeconomic indicators, is associated with a greater job outflow rate. Yet, the adjusted R-squared of the symmetric model is lower than the adjusted R-squared of a model that includes both β_{SU} and β_{SD}, suggesting that the asymmetry of cost behavior is important in predicting gross job outflows. The difference in the adjusted R-squared between the two models is highly statistically significant (1.2% level).

Finally, Columns V and VI repeat the analysis for explaining the net job outflow rate. As was the case for gross job outflows, we find that the adjusted R-squared of the symmetric model is lower than the adjusted R-squared of the asymmetric model. This difference is statistically significant with a p-value of 2.3%.

Overall, the findings in Table 7 provide strong support for the importance of the asymmetric cost model in explaining job outflows. Using both β_{SU} and β_{SD} explains a greater proportion of job outflow variation compared with β_{SYM}.

5. Vector Autoregression (VAR) Analysis

We augment the OLS regression analysis with reduced-form vector autoregression (VAR) models corresponding to the six regressions in Tables 3 and 4. The VAR models build on Okun's law, which predicts a negative relationship between unemployment and real GDP growth. We decompose the unemployment rate into the gross job inflow rate and the gross job outflow rate, and add the variables of interest — that is, β_{SU}, and β_{SD}. We use four lags. We add β_{SU}, and β_{SD} to the VAR individually as well as jointly. We estimate different VAR models as follows:

$$AZ_t = \phi Z_{t-k} + \varepsilon_t, \tag{4}$$

where $Z_t = (Job\ flow\ rate_{t,}\ GDP_{t,}\ \beta_{SU,t,}\ \beta_{SD,t})'$ is a vector of variables that includes (in this order) job-flow rate, real GDP growth rate (*GDP*), β_{SU}, and/or β_{SD}.

In Panel A of Table 8, we consider the gross job inflow rate, modeled using two separate VAR systems. The fist system includes β_{SU} and the second includes β_{SD}.

We present two orthogonalized impulse-response graphs. The first graph depicts the impact of an exogenous shock to β_{SU} on the gross job inflow rate. A one-standard-deviation shock to β_{SU} leads to an increase in the gross job inflow rate of 7 basis points. The shock persists (i.e., is reliably positive within a 95% confidence band) for up to 4 quarters. The second graph depicts the impact of an exogenous shock to β_{SD} on the gross job inflow rate. We find that β_{SD} has no significant impact on the gross job inflow rate.

In Panel B we consider a VAR system that includes both coefficients (i.e., β_{SU} and β_{SD}). The first graph indicates that a one-standard-deviation shock to β_{SU} leads to an increase in the gross job inflow rate of 8 basis points. The shock persists for up to 4 quarters. At the same time, as indicated in the second graph of panel B, a one-standard-deviation shock to β_{SD} leads to a reduction in gross job inflow rate of 5 basis points. This shock lasts for 2 quarters and then dissipates.

Overall, the findings in Table 8 are consistent with the findings in Table 3 and provide strong support for the different information content of β_{SU} and β_{SD} in explaining the gross job inflow rate.

In Table 9, we repeat the analysis in Table 8, with future gross job outflow rate as the job flow variable in the VAR model. In Panel A, we consider the gross job outflow rate, modeled using two separate VAR systems, including β_{SU} and β_{SD}, respectively, while in Panel B, we include both variables in the same system.

The first graph in Table 9, panel A shows that there is no significant relationship between β_{SU} and gross job outflow rate. In the second graph, a one-standard-deviation exogenous shock to

β_{SD} leads to a decrease in the gross job outflow rate of 5 basis points, which lasts up to 2 quarters. In Panel B, a one-standard-deviation shock to β_{SU} leads to a 7 basis points increase in gross job outflow rate, which persists for up to 3 quarters. At the same time, a one-standard-deviation shock to β_{SD} leads to a reduction in gross job outflow rate of 6 basis points, lasting for up to 2 quarters.

Overall, the findings in Table 9 are consistent with the findings in Table 4 and provide strong support for the different information content of β_{SU} and β_{SD} in explaining the gross job outflow rate. Moreover, the impact of β_{SU} and β_{SD} on the gross job outflow rate is less persistent than the impact of these coefficients on the gross job inflow rate.

6. Aggregate Cost Behavior, Job Flow Rates and The Adoption of Wrongful-Discharge Laws (WDLs)

Next, we compare the explanatory power of β_{SU} and β_{SD} in different states. In particular, we classify states according to the adoption of Wrongful Discharge Laws (WDLs). The U.S. has long had a legal presumption that workers can be dismissed at will—that is for any reason (without having to establish "just cause" for termination), and without warning. Since the 1970s, the vast majority of U.S. states have adopted common law exceptions to the employment-at-will doctrine. [9] These exceptions are part of the common law, that is, law created by court decisions (in this case, state courts). We refer to these common-law exceptions as wrongful-discharge laws (hereinafter WDLs). The exceptions are:

(1) *The public policy exception*, which provides workers with protections against discharges that would inhibit them from acting in accordance with public policy, such as performing jury duty, filing a worker's compensation claim, reporting an employer's

[9] See Walsh and Schwarz (1996), Autor (2003), Autor, Donohue, and Schwab (2006), Littler (2009) and Serfling (2016) for detailed discussion.

wrongdoing, or refusing to commit perjury.

(2) *The good faith exception,* which forbids employers from firing workers for 'bad cause.'

(3) *The implied contract exception*, which becomes effective when an employer implicitly promises not to terminate a worker without good cause.

WDLs impose substantial firing costs on employers and hence increase the level of labor adjustment costs. We employ the state-level BED data and estimate the gross job inflow and outflow rates in states that adopted WDLs and states that did not. In determining the dates in which each state has passed each of the above exceptions, we follow Serfling (2016).

We test the ability of aggregate-level β_{SU} and β_{SD} to explain the job flows in the two types of states. We expect that the ability of β_{SU} to explain gross job inflow rates is greater in states that did not adopt the WDLs, as firms in states with WDLs are more likely to consider the potential firing costs and hence, for a given growth rate in GDP, limit the number of newly-hired employees, compared with the number implied by β_{SU}. In contrast, we expect that the ability of β_{SD} to explain gross job outflow rates is greater in states that adopted these laws. In these states, employers are more likely to retain more employees, due to the larger firing costs.[10]

Table 10 reports the results. Panel A compares the ability of β_{SU} to explain the gross job inflow rates in states that adopted (Column I) and did not adopt (Column II) the WDLs. We find that the coefficient of β_{SU} is larger in states that did not adopt these laws, in line with our

[10] We expect that WDLs are likely to affect the calculation of β_{SU} and β_{SD} of firms that reside in states that did and did not adopt these laws. To avoid this potential circularity, we use the elasticities estimated for the entire sample as the independent variables in our analysis.

expectations. The difference in β_{SU} coefficients between the two types of states is statistically significant at the 6% level.

In Panel B, we conduct a parallel analysis comparing the ability of β_{SD} to explain gross job outflow rates between the two types of states. Confirming our expectations, we find that the coefficient of β_{SD} is larger in states that adopted these laws (Column I) compared with sates that did not (Column II). The difference is statistically significant at the 6% level.

7. Summary and conclusions

A growing body of literature, beginning with ABJ (2003), studies cost behavior and assumes a non-symmetric relation between costs and activities: costs increase more when activity rises than they decrease when activity falls by an equivalent amount. We examine the information content of the two aggregate-level elasticities of costs with respect to sales in firms' asymmetric cost function. Both aggregate-level coefficients are highly persistent. Additionally, Consistent with our expectations, we find that the persistence of the aggregate elasticity of costs is higher for sales increases (β_{SU}) than for sales decreases (β_{SD}).

Next, we examine information content with respect to the labor market, using the Business Employment Dynamics (BED) quarterly data on job flows. These data were recently made publicly available by the Bureau of Labor Statistics (BLS). We find that, conditional on the growth in GDP and other macroeconomic indicators, the aggregate elasticity of costs with respect to sales increases (β_{SU}) explains the gross job inflow rate, but not the gross job outflow rate. Conversely, the aggregate elasticity of costs with respect to sales decreases (β_{SD}) explains the gross job outflow rate, but not the gross job inflow rate. When we include both elasticities in the regression, both are significant, but with opposite signs. Moreover, both economic and statistical significance increase in the combined model. We repeat the analysis using vector autoregression (VAR) models and document similar results.

Next, we examine whether the explanatory power of the elasticity of costs with respect to a decrease in sales (β_{SD}) is greater in periods of high uncertainty. We measure the level of uncertainty using the standard error of the estimated β_{SD} coefficient (SE(β_{SD})). The higher this standard error, the less precise is β_{SD} and the higher is the dispersion among different firms in their level of resource retention, reflecting different opinions about future macroeconomic conditions. We find that, conditional on the level of β_{SD}, a higher standard error of β_{SD} is associated with a lower gross job outflow rate, indicating greater employee retention in periods of high uncertainty.

Finally, we compare the model assuming asymmetric cost behavior (i.e., sticky costs) to a traditional model that assumes symmetry. To do so, we estimate the time series of $\beta_{SYM},$ which assumes a symmetric relation between the change in costs and the change in sales. Our findings indicate that, conditional on macroeconomic indicators and for a given level of GDP growth, a larger β_{SYM} is associated with both greater job outflows and job inflows. Moreover, the explanatory power of a model that includes β_{SYM} is lower than the explanatory power of a model that includes both β_{SD} and β_{SU}, when explaining the gross job outflow rate, but not the gross job inflow rate, consistent with the information content of β_{SD} reflecting the sticky nature of costs.

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Appendix A
Definitions of key variables

β_1 and β_2 coefficient estimates	Estimated coefficients obtained from running the following ordinary least squares regression cross-sectionally each quarter q using Compustat quarterly data for quarters [q–3, q]: $$\log\left[\frac{(COGS+SG\&A)}{lag(COGS+SG\&A)}\right] = \beta_0+\beta_1\log\left[\frac{SALES}{lag(SALES)}\right] + \beta_2 I\_Decrease\times\log\left[\frac{SALES}{lag(SALES)}\right]+\varepsilon$$
β_3 coefficient estimates	Estimated coefficients obtained from running the following ordinary least squares regression cross-sectionally each quarter q using Compustat quarterly data for quarters [q–3, q]: $$\log\left[\frac{(COGS+SG\&A)}{lag(COGS+SG\&A)}\right] = \beta_0+\beta_1\log\left[\frac{SALES}{lag(SALES)}\right]+\varepsilon$$
β_{SU}	β_1 coefficient estimates, standardized by subtracting sample mean and dividing by standard deviation.
β_{SD}	β_2 coefficient estimates × –1, standardized by subtracting sample mean and dividing by standard deviation.
β_{SYM}	β_3 coefficient estimates, normalized by subtracting its sample mean and dividing by standard deviation.
Gross job inflow/outflow rate	Gross job inflow or outflow for the total private sector in the U.S. as a percentage of total employment in this sector, retrieved from the Bureau of Labor Statistics.
Net job outflow rate	Gross job outflow rate minus gross job inflow rate.
Real GDP growth rate (*GDP*)	Real GDP growth rate.
Aggregate earnings (*Earn*)	Value-weighted average earnings (scaled by contemporaneous sales) in each quarter, with weights based on market capitalization as of the beginning of the quarter. Aggregate GAAP earnings each quarter are the cross-sectional value-weighted averages of earnings (scaled by contemporaneous sales), following the procedure described in Konchitchki and Patatoukas (2014).
Market return (*MktRet*)	Equal-weighted average quarterly market return for the stocks in the sample.
Industrial production index (*IPI*)	Industrial production index from the Federal Reserve Bank of St. Louis.
BBD Economic Policy Uncertainty (*EPU*) index	Economic policy uncertainty index obtained from www.policyuncertainty.com and based on Baker, Bloom, and Davis (2014). This index is constructed from three underlying components—disagreement among economic forecasters, the number of federal-tax-code provisions set to expire in future years, and newspaper coverage of policy-related economic uncertainty.

Consumer Sentiment Index (*CSI*)	Index of consumer sentiment based on surveys of consumers by the University of Michigan. This index is constructed from a national representative survey based on telephonic household interviews and captures short-term consumer attitudes about the business climate, spending, and personal finance.
4-week average of unemployment insurance weekly claims (*UIC*)	4-week average of unemployment insurance weekly claims released by the U.S. Department of Labor Employment & Training Administration.
Help-Wanted Index (*HWI*)	Composite Help-Wanted Index, captures the job opening rate, which equals the number of job openings or vacancies divided by the size of the labor force.
Employment growth dispersion (*EmpG_Disp*)	Sector-level employment growth dispersion available in quarter t, measured as residual from an AR(2) model: $AggEmpGDisp_t = r_0 + r_1\, AggEmpGDisp_{t-1} + r_2\, AggEmpGDisp_{t-2} + e_t,$ where $AggEmpGDisp_{t-k}$ is aggregate employment growth dispersion estimate for quarter $t-k$. (See Nallareddy and Ogneva 2017).
Stock return dispersion (*Ret_Disp*)	Stock return dispersion available in quarter t, measured as the residual from an AR(2) model: $AggRetDisp_t = r_0 + r_1\, AggRetDisp_{t-1} + r_2\, AggRetDisp_{t-2} + e_t,$ where $AggRetDisp_{t-k}$ is aggregate stock return dispersion estimate for quarter $t-k$.
Effective Federal Funds rate (*IR*)	Federal funds rate released by the Federal Reserve Bank of New York.
Inflation (*Inf*)	Quarterly average of monthly annualized changes in chain-weighted GDP price index.

Table 1. Descriptive statistics

Panel A: Summary statistics

	Mean	Median	SD
Gross job inflow rate %	7.107	7.000	0.823
Gross job outflow rate %	6.790	6.800	0.746
Net job outflow rate %	-0.317	-0.400	0.597
β_1 coefficient estimates	0.410	0.385	0.108
β_2 coefficient estimates	-0.053	-0.064	0.088
β_3 coefficient estimates	0.392	0.375	0.089
GDP	2.531	2.612	1.952
Earn	0.072	0.082	0.041
Δ*Earn*	-0.101	-0.061	0.220
MktRet	0.029	0.031	0.125
IPI	92.290	95.217	11.333
EPU	106.053	97.855	31.722
CSI	87.491	90.000	12.264
UIC	0.357	0.340	0.071
IR	2.673	2.302	2.264
Inf	1.920	1.950	0.840
HWI	2.797	2.827	0.599
EmpG_Disp	-0.083	-0.136	0.289
Ret_Disp	0.019	0.009	0.080

Panel B: Pairwise Pearson correlations – job flow rates and unemployment rate change

	ChUR	Net job outflow rate	Gross job inflow rate	Gross job outflow rate
ChUR	1			
Net job outflow rate	0.816***	1		
Gross job inflow rate	-0.226**	-0.486***	1	
Gross job outflow rate	0.404***	0.265***	0.714***	1

Table shows descriptive statistics for the main variables. The sample consists of 100 calendar quarterly observations ranging from Q3:1992 to Q2:2017. Composite Help-Wanted Index is available until Q4:2016, we use the latest updated value of the index for Q1:2017 and Q2:2017. Panel A shows summary statistics for the main variables. Panel B shows pairwise correlations between the BED job flow rates and the change in the traditional unemployment rate (*ChUR*), which is based on the Current Population Survey. Variables are as defined in Appendix A. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 2. The persistence of aggregate cost behavior

	I	II
	$\beta_{SU\ t+1}$	$\beta_{SD\ t+1}$
$\beta_{SU\ t}$	0.990***	
	(53.008)	
$\beta_{SD\ t}$		0.931***
		(18.811)
Intercept	-0.022	0.001
	(-1.064)	(0.020)
Adjusted R-squared	0.973	0.864
Observations	100	100
Suest chi2-statistic	(I) vs (II): 3.65**	
(*p*-value)	[0.056]	

Table reports the results of OLS regressions of aggregate cost behavior components on its own lags. We compare the statistical difference in the magnitude of β_{SU} and β_{SD} at the bottom of the table. Variables are as defined in Appendix A. *t*-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 3. Association between aggregate cost behavior and the gross job inflow rate--Contemporaneous relationship

	I	II	III
	Gross job inflow rate	Gross job inflow rate	Gross job inflow rate
β_{SU}	0.380***		0.634***
	(3.849)		(8.112)
β_{SD}		0.021	-0.184***
		(0.423)	(-3.959)
GDP	0.065***	0.083***	0.054***
	(3.413)	(3.638)	(2.854)
Earn	0.775	0.653	0.800
	(0.754)	(0.691)	(0.944)
Δ*Earn*	-0.160	-0.199	-0.160
	(-0.837)	(-1.104)	(-0.933)
MktRet	-0.689*	-0.878**	-0.386*
	(-1.922)	(-2.329)	(-1.723)
IPI	-0.020***	-0.037***	-0.014***
	(-4.169)	(-10.448)	(-3.465)
EPU	0.000	0.001	0.001
	(0.387)	(0.387)	(0.468)
CSI	0.014***	0.021***	0.007*
	(2.894)	(4.648)	(1.881)
UIC	1.554**	0.807	0.002
	(2.239)	(0.892)	(0.003)
HWI	0.104	0.071	0.085
	(1.113)	(0.574)	(0.916)
EmpG_Disp	-0.104	-0.127	-0.062
	(-1.305)	(-1.167)	(-0.821)
Ret_Disp	1.244***	1.544***	0.812**
	(2.945)	(3.589)	(2.322)
IR	0.035*	0.093***	0.022
	(1.667)	(3.804)	(1.205)
Inf	0.069**	0.082**	0.084***
	(2.031)	(2.134)	(2.705)
Intercept	6.382***	7.410***	7.034***
	(9.576)	(9.815)	(8.997)
Adjusted R-squared	0.924	0.904	0.935
Observations	100	100	100

Table reports the results of OLS regressions of gross job inflow rate on β_{SU} and β_{SD} estimated in the current quarter q, using public firms' accounting data from quarter [q-3, q]. Variables are as defined in Appendix A. t-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 4. Association between aggregate cost behavior and the gross job outflow rate--Contemporaneous relationship

	I	II	III
	Gross job outflow rate	Gross job outflow rate	Gross job outflow rate
β_{SU}	-0.083		0.316***
	(-0.752)		(2.774)
β_{SD}		-0.187***	-0.289***
		(-3.971)	(-4.583)
GDP	-0.021	-0.023	-0.037*
	(-0.955)	(-1.145)	(-1.750)
Earn	-3.153**	-3.187***	-3.114***
	(-2.294)	(-2.843)	(-2.776)
Δ*Earn*	-0.348**	-0.367***	-0.348**
	(-2.029)	(-2.720)	(-2.527)
MktRet	-0.937**	-0.705*	-0.460
	(-2.068)	(-1.920)	(-1.429)
IPI	-0.025***	-0.026***	-0.015**
	(-4.564)	(-6.992)	(-2.564)
EPU	-0.003*	-0.003*	-0.003*
	(-1.830)	(-1.978)	(-1.915)
CSI	0.016*	0.012*	0.005
	(1.779)	(1.678)	(0.683)
UIC	5.908***	3.869***	3.468***
	(5.675)	(3.810)	(3.379)
HWI	0.084	0.047	0.054
	(0.635)	(0.363)	(0.394)
EmpG_Disp	0.115	0.148	0.181
	(0.797)	(1.018)	(1.170)
Ret_Disp	1.166	0.851	0.486
	(1.500)	(1.292)	(0.838)
IR	0.147***	0.161***	0.126***
	(7.138)	(7.323)	(5.862)
Inf	0.073	0.095**	0.096**
	(1.448)	(2.147)	(2.167)
Intercept	5.325***	6.537***	6.350***
	(4.880)	(5.910)	(5.628)
Adjusted R-squared	0.842	0.866	0.874
Observations	100	100	100

Table reports the results of OLS regressions of gross job outflow rate on β_{SU} and β_{SD} estimated in the current quarter *q*, using public firms' accounting data from quarter [*q*-3, *q*]. Variables are as defined in Appendix A. *t*-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 5. Association between aggregate cost behavior and future gross job flow rate--Prediction

Panel A: Association between β_{SU}, β_{SD} and future gross job inflow rates

	I				II				III			
	Gross job inflow rate$_{t+k}$				Gross job inflow rate$_{t+k}$				Gross job inflow rate$_{t+k}$			
	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
β_{SU}	0.327***	0.357***	0.372***	0.328***					0.593***	0.653***	0.706***	0.621***
	(3.953)	(3.341)	(3.039)	(2.666)					(7.101)	(7.349)	(7.005)	(6.469)
β_{SD}					0.009	0.009	0.001	0.001	-0.170***	-0.189***	-0.213***	-0.187***
					(0.233)	(0.193)	(0.011)	(0.012)	(-4.077)	(-3.986)	(-3.839)	(-3.454)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.919	0.914	0.910	0.912	0.906	0.898	0.893	0.899	0.928	0.925	0.924	0.923
Observations	96	96	96	96	96	96	96	96	96	96	96	96

Panel B: Association between β_{SU}, β_{SD} and future gross job outflow rates

	I				II				III			
	Gross job outflow rate$_{t+k}$				Gross job outflow rate$_{t+k}$				Gross job outflow rate$_{t+k}$			
	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
β_{SU}	-0.042	-0.058	-0.044	-0.177					0.494***	0.394*	0.414*	0.252
	(-0.273)	(-0.425)	(-0.362)	(-1.393)					(3.307)	(1.837)	(1.910)	(1.573)
β_{SD}					-0.193***	-0.169***	-0.167**	-0.198**	-0.342***	-0.288***	-0.293**	-0.274**
					(-3.694)	(-3.009)	(-2.493)	(-2.619)	(-4.595)	(-2.728)	(-2.437)	(-2.488)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.809	0.801	0.783	0.811	0.839	0.823	0.804	0.836	0.856	0.833	0.816	0.839
Observations	96	96	96	96	96	96	96	96	96	96	96	96

Table reports the results of OLS regressions of future gross job flow rate on β_{SU} and β_{SD} estimated in the current quarter q, using public firms' accounting data from quarter [q-3, q]. Panel A reports the results of OLS regressions of future gross job inflow rate on β_{SU} and β_{SD} up to 4 quarters. Panel B reports the results of OLS regressions of future gross job outflow rate on β_{SU} and β_{SD} up to 4 quarters. Variables are as defined in Appendix A. t-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Figure 1. Standard errors of β_{SD} and the Economic Policy Uncertainty index

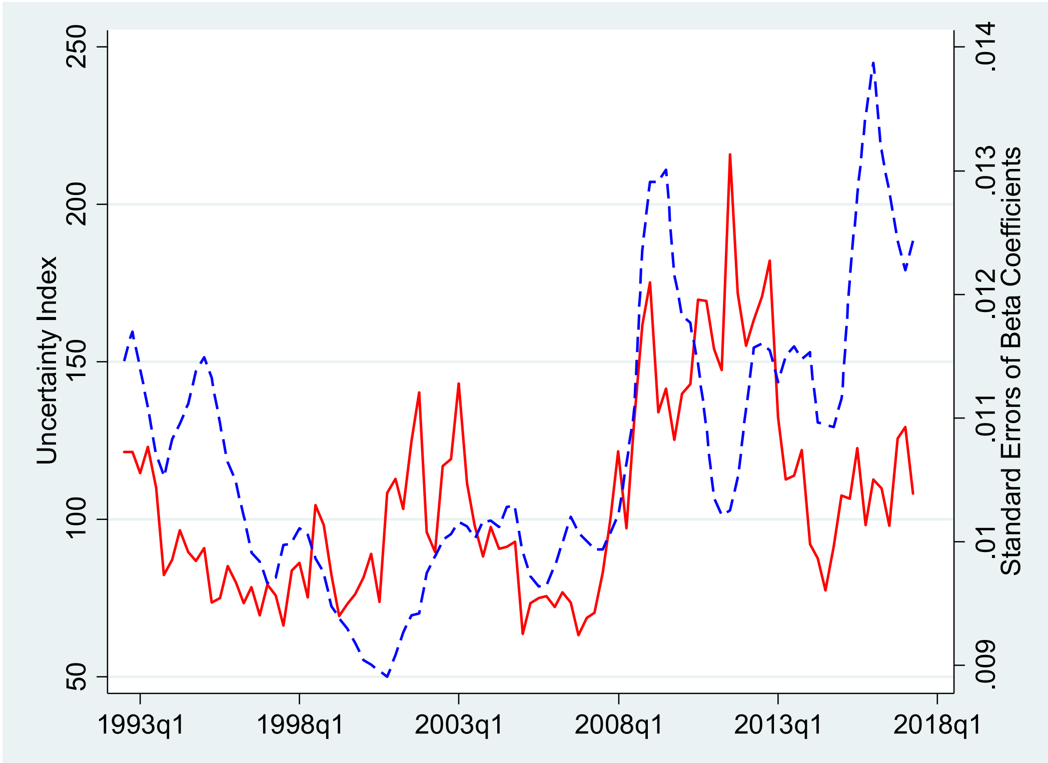


Figure shows BBD Economic Policy Uncertainty Index (in solid line) and standard errors of β_{SD} (in dash line) for the period Q3:1992 to Q2:2017.

Table 6. Association between β_{SD}, standard error of β_{SD}, and gross job outflow rate

	I Gross job outflow rate	II Gross job outflow rate
β_{SD}	-0.217***	-0.208***
	(-4.764)	(-5.683)
SE(β_{SD})—top decile	-0.329**	
	(-1.997)	
β_{SD} × SE(β_{SD})—top decile	-0.248**	
	(-2.430)	
SE(β_{SD})—top quartile		-0.295***
		(-3.879)
β_{SD} × SE(β_{SD})—top quartile		-0.103*
		(-1.846)
GDP	-0.018	-0.042**
	(-0.907)	(-2.188)
Earn	-3.122***	-3.151***
	(-2.763)	(-2.990)
Δ*Earn*	-0.368***	-0.354***
	(-2.691)	(-2.844)
MktRet	-0.719**	-0.441
	(-2.026)	(-1.269)
IPI	-0.029***	-0.030***
	(-7.208)	(-10.105)
EPU	-0.003*	-0.002
	(-1.970)	(-1.507)
CSI	0.010	0.011
	(1.405)	(1.651)
UIC	3.464***	3.068***
	(3.064)	(2.976)
HWI	0.194	0.151
	(1.232)	(1.227)
EmpG_Disp	0.136	0.129
	(0.892)	(0.925)
Ret_Disp	0.761	0.473
	(1.246)	(0.811)
IR	0.134***	0.136***
	(5.914)	(6.345)
Inf	0.111**	0.080**
	(2.468)	(2.029)
Intercept	6.798***	7.143***
	(6.342)	(7.335)
Adjusted R-squared	0.873	0.880
Observations	100	100

Table reports the results of OLS regressions of job outflow rates on β_{SD}, the standard error of β_{SD}, their interactions, and control variables. β_{SD} is estimated for each quarter *q* using public firms' accounting data from quarters [*q*-3, *q*]. SE(β_{SD})—top decile (quartile) is a dummy variable that takes a value of 1 if SE(β_{SD}) is in the highest decile (quartile) and 0 otherwise. Other variables are as defined in Appendix A. *t*-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 7. A comparison of the symmetric and asymmetric cost models

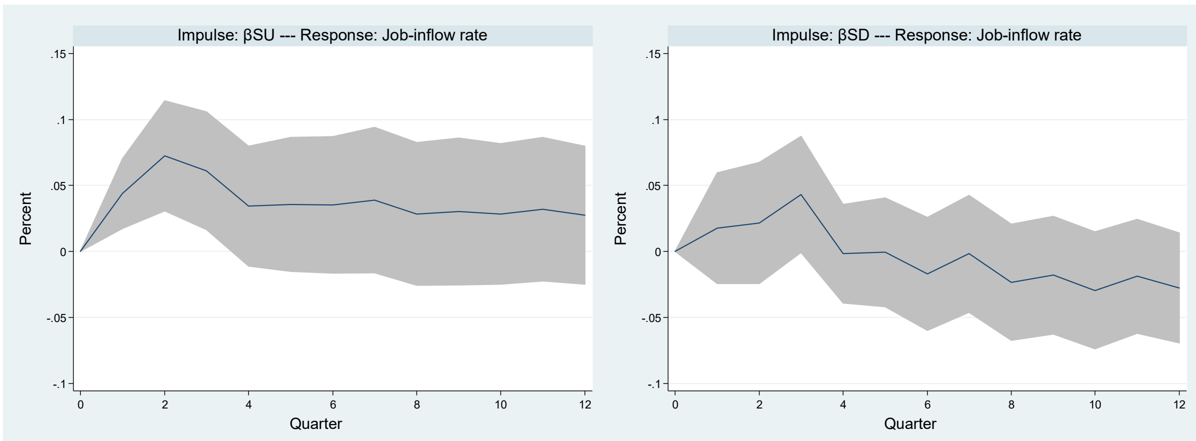
	I Gross job inflow rate	II Gross job inflow rate	III Gross job outflow rate	IV Gross job outflow rate	V Net job outflow rate	VI Net job outflow rate
β_{SU}	0.634***		0.316***		-0.318**	
	(8.112)		(2.774)		(-2.488)	
β_{SD}	-0.184***		-0.289***		-0.105*	
	(-3.959)		(-4.583)		(-1.726)	
β_{SYM}		0.551***		0.285**		-0.267*
		(7.989)		(2.259)		(-1.872)
GDP	0.054***	0.053***	-0.037*	-0.041*	-0.091***	-0.093***
	(2.854)	(2.777)	(-1.750)	(-1.893)	(-3.731)	(-3.601)
Earn	0.800	0.940	-3.114***	-2.973**	-3.914***	-3.914***
	(0.944)	(1.114)	(-2.776)	(-2.078)	(-4.170)	(-3.631)
Δ*Earn*	-0.160	-0.186	-0.348**	-0.331*	-0.188	-0.145
	(-0.933)	(-1.116)	(-2.527)	(-1.857)	(-1.325)	(-0.953)
MktRet	-0.386*	-0.313	-0.460	-0.620	-0.074	-0.307
	(-1.723)	(-1.461)	(-1.429)	(-1.607)	(-0.203)	(-0.787)
IPI	-0.014***	-0.013***	-0.015**	-0.009	-0.001	0.005
	(-3.465)	(-3.451)	(-2.564)	(-1.434)	(-0.163)	(0.684)
EPU	0.001	0.001	-0.003*	-0.003	-0.003*	-0.003*
	(0.468)	(0.553)	(-1.915)	(-1.627)	(-1.946)	(-1.723)
CSI	0.007*	0.006	0.005	0.007	-0.002	0.001
	(1.881)	(1.474)	(0.683)	(0.752)	(-0.279)	(0.158)
UIC	0.002	-0.556	3.468***	5.551***	3.466***	6.108***
	(0.003)	(-0.789)	(3.379)	(4.886)	(3.128)	(5.388)
HWI	0.085	0.081	0.054	0.100	-0.032	0.019
	(0.916)	(0.845)	(0.394)	(0.667)	(-0.255)	(0.135)
EmpG_Disp	-0.062	-0.049	0.181	0.157	0.242	0.207
	(-0.821)	(-0.660)	(1.170)	(0.966)	(1.439)	(1.152)
Ret_Disp	0.812**	0.746**	0.486	0.709	-0.326	-0.037
	(2.322)	(2.029)	(0.838)	(1.075)	(-0.504)	(-0.048)
IR	0.022	0.017	0.126***	0.092***	0.104***	0.075***
	(1.205)	(0.978)	(5.862)	(3.254)	(4.492)	(2.989)
Inf	0.084***	0.091***	0.096**	0.072	0.012	-0.019
	(2.705)	(2.839)	(2.167)	(1.434)	(0.288)	(-0.379)
Intercept	7.034***	7.307***	6.350***	4.927***	-0.684	-2.380**
	(8.997)	(10.608)	(5.628)	(4.355)	(-0.708)	(-2.274)
Adjusted R-squared	0.935	0.935	0.874	0.851	0.742	0.695
Observations	100	100	100	100	100	100
Vuong z-statistic	(I) vs (II): 0.355		(III) vs (IV): 2.519**		(V) vs (VI): 2.276**	
(p-value)	[0.722]		[0.012]		[0.023]	

Table reports the results of OLS regressions of job flow rates on β_{SU}, β_{SD} and β_{SYM}, estimated in the current quarter q, using public firms' accounting data from quarters [q-3, q]. z-statistics following Vuong tests are presented at the bottom of each pair of columns to show the differences in R-squared between models that include β_{SU} and β_{SD} and models that include β_{SYM}. p-values are shown in square brackets underneath the z-statistics. Variables are as defined in Appendix A. t-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.

Table 8. Association between β_{SU}, β_{SD} and future gross job inflow rates – Vector autoregression models

Panel A: Impulse-response graph to shock in cost behavior components — β_{SU} and β_{SD} separately

$$AZ_t = \phi Z_{t-k} + \varepsilon_t, \text{ where } Z_t = \left(Job\ Inflow\ Rate_{t,}\ GDP_{t,}\ \beta_{SU_t}/\beta_{SD_t}\right)'$$



Panel B: Impulse-response graph to shock in cost behavior components — β_{SU} and β_{SD} jointly

$$AZ_t = \phi Z_{t-k} + \varepsilon_t, \text{ where } Z_t = \left(Job\ Inflow\ Rate_{t,}\ GDP_{t,}\ \beta_{SU_t},\ \beta_{SD_t}\right)'$$

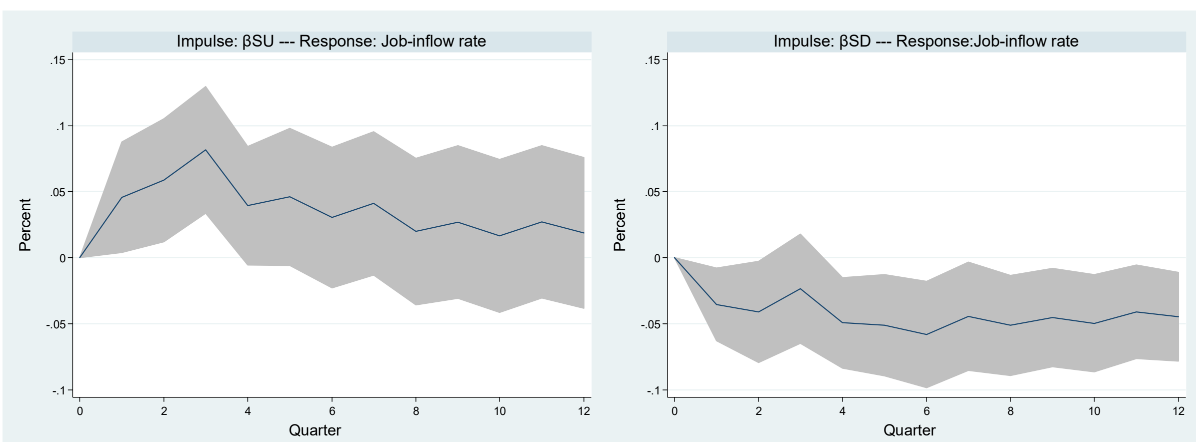
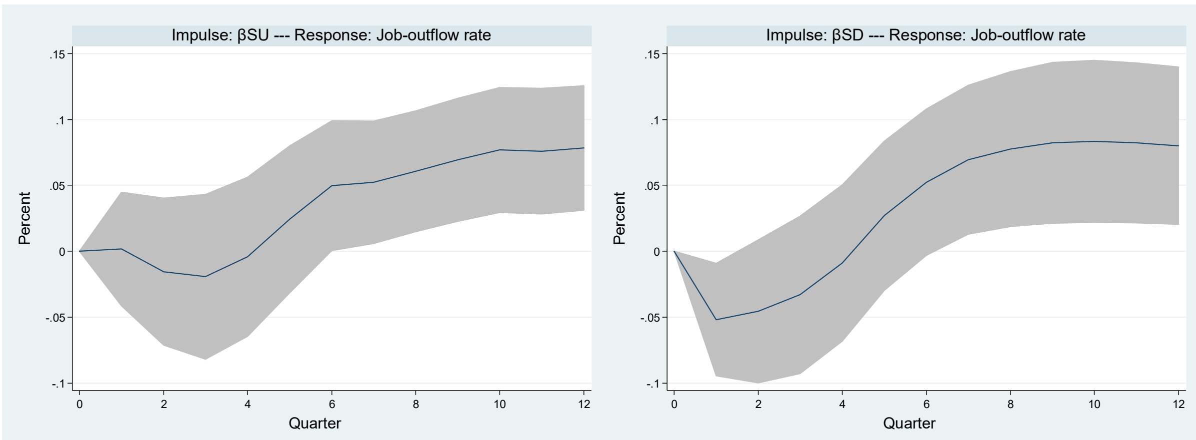


Table reports the results of reduced-form VAR models with 4 lags including the following variables: gross job inflow rate (*Job Inflow Rate*), real GDP growth rate *(GDP)*, β_{SU}, and β_{SD}. Panel A shows the impulse-response function (IRF) graphs for the response of gross job inflow rate to a one-standard-deviation shock to β_{SU} and β_{SD} from VAR models that include β_{SU} and β_{SD} separately. Panel B shows the impulse-response function (IRF) graph for the response of gross job inflow rate to a one-standard-deviation shock to β_{SU} and β_{SD} from a VAR model that includes β_{SU} and β_{SD} jointly. 95% confidence bands are also presented (shaded areas). Variables are defined in Appendix A.

Table 9. Association between β_{SU}, β_{SD} and future gross job outflow rates – Vector autoregression models

Panel A: Impulse-response graph to shock in cost behavior components —β_{SU} and β_{SD} separately

$$AZ_t = \phi Z_{t-k} + \varepsilon_t, \text{ where } Z_t = \left(Job\ Outflow\ Rate_t,\ GDP_t,\ \beta_{SU_t}/\beta_{SD_t}\right)'$$



Panel B: Impulse-response graph to shock in cost behavior components —β_{SU} and β_{SD} jointly

$$AZ_t = \phi Z_{t-k} + \varepsilon_t, \text{ where } Z_t = \left(Job\ Outflow\ Rate_t,\ GDP_t,\ \beta_{SU_t},\ \beta_{SD_t}\right)'$$

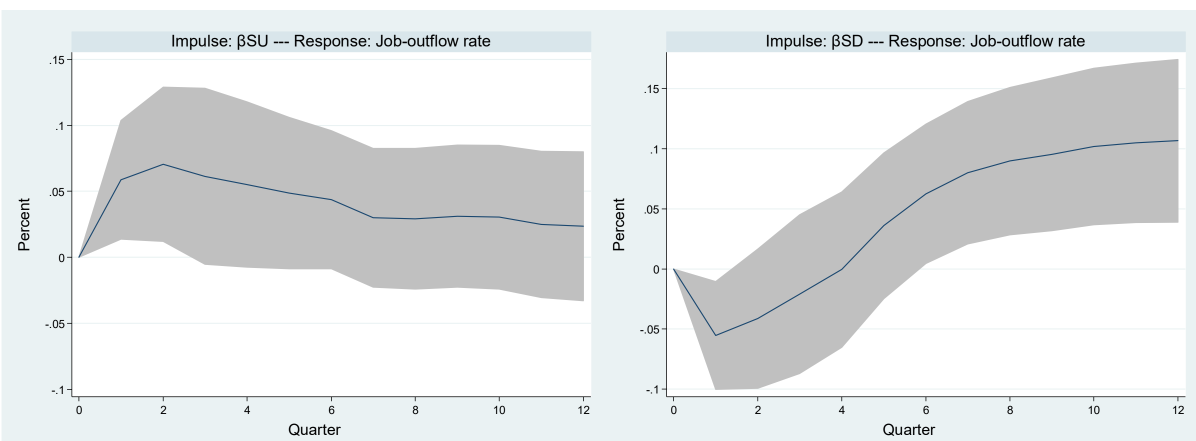


Table reports the results of reduced-form VAR models with 4 lags including the following variables: gross job outflow rate (*Job Outflow Rate*), real GDP growth rate *(GDP)*, β_{SU}, and β_{SD}. Panel A shows the impulse-response function (IRF) graphs for the response of gross job outflow rate to a one-standard-deviation shock to β_{SU} and β_{SD} from VAR models that include β_{SU} and β_{SD} separately. Panel B shows the impulse-response function (IRF) graph for the response of gross job outflow rate to a one-standard-deviation shock to β_{SU} and β_{SD} from a VAR model that includes β_{SU} and β_{SD} jointly. 95% confidence bands are also presented (shaded areas). Variables are defined in Appendix A.

Table 10. The association between aggregate cost elasticities and job flow rates

— Different state-level labor protection

Panel A: β_{SU} and gross job-inflow rate

State-level labor protection	I High	II Low
β_{SU}	0.386***	0.490***
	(2.747)	(4.457)
GDP	0.066**	0.083***
	(2.220)	(4.171)
$Earn_t$	1.686	0.520
	(1.027)	(0.447)
$\Delta Earn_t$	-0.298	-0.149
	(-0.950)	(-0.689)
$MktRet_t$	-0.835	-0.697*
	(-1.539)	(-1.712)
IPI_t	-0.024***	-0.025***
	(-3.193)	(-4.813)
$Uncer_t$	-0.000	0.002
	(-0.168)	(1.171)
CSI_t	0.024***	0.014***
	(3.181)	(2.671)
UIC_t	2.140**	1.392*
	(2.053)	(1.686)
HWI_t	0.096	0.123
	(0.609)	(1.135)
$EmpG\_Disp_t$	-0.197*	-0.053
	(-1.714)	(-0.572)
Ret_Disp_t	1.520**	1.380***
	(2.399)	(2.925)
IR_t	0.046	0.046*
	(1.543)	(1.833)
Inf_t	0.112*	0.070*
	(1.883)	(1.964)
Intercept	-1.592	-0.404
	(-1.425)	(-0.542)
Adjusted R-squared	0.887	0.930
Observations	100	100
Suest chi2-statistic	(I) vs (II): 3.44*	
(*p*-value)	[0.064]	

Panel B: β_{SD} and gross job-outflow rate

State-level labor protection	I High	II Low
β_{SD}	-0.283***	-0.212***
	(-3.626)	(-3.250)
GDP	-0.024	-0.035
	(-0.734)	(-1.409)
$Earn_t$	-3.384**	-4.721***
	(-2.052)	(-4.031)
$\Delta Earn_t$	-0.523*	-0.406**
	(-1.781)	(-2.390)
$MktRet_t$	-0.859	-0.878*
	(-1.343)	(-1.926)
IPI_t	-0.033***	-0.036***
	(-4.565)	(-7.209)
$Uncer_t$	-0.005**	-0.003
	(-2.511)	(-1.518)
CSI_t	0.012	0.019**
	(0.995)	(2.152)
UIC_t	3.968**	5.853***
	(2.376)	(4.438)
HWI_t	-0.103	0.159
	(-0.452)	(0.922)
$EmpG\_Disp_t$	0.323	0.216
	(1.473)	(1.171)
Ret_Disp_t	1.088	1.182
	(1.242)	(1.430)
IR_t	0.243***	0.199***
	(7.209)	(6.029)
Inf_t	0.137*	0.131**
	(1.825)	(2.343)
Intercept	0.810	-0.993
	(0.415)	(-0.710)
Adjusted R-squared	0.822	0.876
Observations	100	100
Suest chi2-statistic	(I) vs (II): 3.59*	
(*p*-value)	[0.058]	

Table reports the results of OLS regressions of job flow rates of firms headquartered in states with high and low labor-protection laws. A high labor-protection state is defined as a state that has adopted the good faith, implied contract, and public policy exceptions as of a given quarter. β_{SU} and β_{SD} estimated in the current quarter, using public firms' accounting data from quarter [t-3,t]. Panel A reports the results of OLS regressions of gross job inflow rates on β_{SU}, while Panel B reports the results of regressing gross job outflow rates on $\beta_{SD.}$ We compare the statistical difference in the explanatory power of β_{SU} and β_{SD} between the two types of states at the bottom of each panel. Variables are defined in Appendix A. *t*-statistics shown in parentheses underneath the estimated coefficients are based on Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with three lags. ***, **, and * indicate two-tailed statistical significance at levels 1%, 5%, and 10%, respectively.